Retrieving Dynamic Origin-Destination Matrices from Bluetooth Data

Gabriel Michau, (corresponding author)
Smart Transport Research Centre,
Faculty of Build Environment and Engineering,
Queensland University of Technology,
2 George St GPO Box 2434, Brisbane QLD 4001 – Australia
Tel: +61 (0)7 31 38 03 75
Gabriel.Michau@qut.edu.au

Dr. Alfredo Nantes,
Smart Transport Research Centre,
Faculty of Build Environment and Engineering,
Queensland University of Technology,
2 George St GPO Box 2434, Brisbane QLD 4001 – Australia
Tel: +61 (0)7 31 38 14 61
A.Nantes@qut.edu.au

Pr. Edward Chung,
Smart Transport Research Centre,
Faculty of Build Environment and Engineering,
Queensland University of Technology,
2 George St GPO Box 2434, Brisbane QLD 4001 – Australia
Tel: +61 (0)7 31 38 11 43
Edward.Chung@qut.edu.au

Dr. Patrice Abry,
Laboratoire de Physique,
École normale supérieure de Lyon,
46, allée d'Italie 69364 Lyon cedex 07 France
Tel: +33 (0)4 72 72 84 93 – Fax: +33 (0)4 72 72 89 50
Patrice.Abry@ens-lyon.fr

Dr. Pierre Borgnat,
Laboratoire de Physique,
École normale supérieure de Lyon,
46, allée d'Italie 69364 Lyon cedex 07 France
Tel: +33 (0)4 72 72 86 91 – Fax: +33 (0)4 72 72 80 80
Pierre.Borgnat@ens-lyon.fr

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ABSTRACT

The Bluetooth technology is being increasingly used, among the Automated Vehicle Identification Systems, to retrieve important information about urban networks. Because the movement of Bluetooth-equipped vehicles can be monitored, throughout the network of Bluetooth sensors, this technology represents an effective means to acquire accurate time dependant Origin Destination information. In order to obtain reliable estimations, however, a number of issues need to be addressed, through data filtering and correction techniques. Some of the main challenges inherent to Bluetooth data are, first, that Bluetooth sensors may fail to detect all of the nearby Bluetooth-enabled vehicles. As a consequence, the exact journey for some vehicles may become a latent pattern that will need to be estimated. Second, sensors that are in close proximity to each other may have overlapping detection areas, thus making the task of retrieving the correct travelled path even more challenging.

The aim of this paper is twofold: to give an overview of the issues inherent to the Bluetooth technology, through the analysis of the data available from the Bluetooth sensors in Brisbane; and to propose a method for retrieving the itineraries of the individual Bluetooth vehicles. We argue that estimating these latent itineraries, accurately, is a crucial step toward the retrieval of accurate dynamic Origin Destination Matrices.

INTRODUCTION

A complete knowledge of travel demand is the cornerstones for many applications from transport demand modelling to design of traffic management schemes *(1)*. In fact, this knowledge can be used to determine whether the network can satisfy the demand, or if ongoing changes will have a significant impact on its use, and therefore on the traffic flows. This knowledge is very hard to acquire for two reasons. First, it can only rest upon the comparison between the current situation and individual's stated preferences *(2–5)* ; or upon forecasting models which make strong assumptions about the evolution of the current state of traffic *(6)*. Secondly, the traffic states themselves are typically deduced from measurements of network parameters. Unfortunately, as these measures are constrained by the existing infrastructures, they might not accurately reflect the real demand. In any case, a good estimate of the present state of the network is key to any mobility analysis, and therefore paramount for transport research. Various indicators, such as travel time, speed, and traffic demand, are often used to describe the state of a road network. Travel time and average speed help quantifying the level of congestion. Similarly, Origin/Destination matrices (OD matrices) are used as indicators of the travel volumes between origin and destination regions of the network, over some pre-defined period of time.

To obtain these OD matrices, the area covered by the network is usually partitioned into smaller geographic zones, represented by their centroids. A *power of attraction* (or a potential of being a destination) and *power of production* (or a potential of being an origin) are then associated to these centroids. OD matrices are typically two-dimensional, with rows and columns denoting the origin and destination points, respectively. The elements of these matrices are the census of the volume of journeys, from origin to destination.

Until now, the Origin Destination matrices have been retrieved through expensive surveys and/or from assignment algorithms *(7, 8)*, which generally use traffic counts to generate OD patterns. Surveys are effective but they are expansive and they capture stated behaviour, as opposed to observed behaviour captured by Automated Vehicle Identification Systems (AVI) and might therefore be biased by the subjective perception of the user on its own journey. On the other hand, Origin Destination Count-Based Estimation relies on strong assumptions, in order to solve undetermined systems when assigning routes consistently with the observed counts.

Recent technological advances, mainly regarding the improvement of computers, have led to the first AVI systems. Amongst these systems, the technologies that are largely used for AVI purposes are plate recognition, GPS and Bluetooth track recording. The Bluetooth technology is being proven to be cost-effective and, therefore, particularly suitable for urban networks. As it enables the detections of the discoverable Bluetooth devices in the surrounding of a sensor, a single Bluetooth sensor could be used to capture the traffic at the intersections, regardless of the direction of travel of the vehicles. Thus, they are easy to install. Moreover, the detection can be carried out anonymously, in that the electronic identifier (or MAC address) of the Bluetooth device in the detected vehicles can be converted into an encrypted (hash) code, at the sensor site. The privacy that the Bluetooth technology can feature is a great advantage, compared to other tracking systems.

RELATED WORK

Bluetooth detector is an AVI technology on which research has already been led for several applications. It has been extensively used as a reliable source for the estimation of travel time along corridor *(9–12)*, due to the large amounts of samples available, and the ease to collect them. However, Wasson et al. *(13)* and Sadabadi et al. *(14)* calculated that the noise on the detection time, on the detection area could be expressed as a uncertainty of around 180m. Thus if this noise might be considered negligible for large inter-detectors lengths, it questions the relevance or reliability of travel time estimation in dense network. Tsubota et al. *(15)* used Bluetooth data for analysing the level of congestion at the intersection, based on the detection time, and the duration of transit at the intersection.

Van Der Zijpp et al. *(16)* discussed the potential of AVI systems for the estimation of Origin-Destination matrices. Since then, further research has been conducted into Bluetooth-based data collection for improving the estimation of these matrices. From the Bluetooth-based travel time analysis, Barceló, Montero et al. amongst other presented methodology to estimate Origin-Destination

Matrices, along corridors *(17)* (freeway with 11 entries and 12 exits) and in urban networks *(18)* with 48 detectors. Blogg, Simler et al. *(19)* did similar work with two cases studies in Brisbane: one with two OD pairs and one with 29 detectors. Yucel, Tuydes-Yaman et al. *(20)* presented a case study in Ankara for an open system composed of 10 intersection and 4 major roads equipped with 4 Bluetooth devices. Carpenter, Fowler et al.*(21)*, discussed a new opportunity offered by Bluetooth sensors, that is, the route specific Origin-Destination matrices estimation. Their work was based on a single case study in Jacksonville with 14 detection devices spread along one corridor.

Most of these previous works are based on the data collected by a limited number of Bluetooth sensors scattered along the network. Therefore, the Origin Destination issues have only been considered over a limited geographical area or had to be combined with other data sources (traffic counts, route assignment algorithm,...).

The availability of more than 260 scanners within the Brisbane urban area creates new opportunities, as far as concerns the retrieval of Origin Destination matrices. This paper aims to present these new challenges and the difficulties that come with these opportunities.

First, this dense network of sensors can directly be used for the zoning of the studied area. Each sensor is considered as a centroid and a geographical zone is then associated with it (for example based on Voronoi partitions). Through this description of the networks, it becomes easy to assign the origin and destination of trips from individual drivers, from the first and last detections observed in the Bluetooth data collected. These first and last detections observed might not correspond to the actual origin and destination of the trips, as the trips might continue outside the Bluetooth covered area. However, the missing information about the complete trip is not critical to our work, as our aim is the analysis of the OD patterns within the urban context.

In addition, if the sensors are deployed at the most crucial intersections, graphs can be used to accurately describe the road network covered by the Bluetooth sensors. Such graphs will have sensors as vertices and links indicating the road links between sensors.

RETRIEVING ORIGIN AND DESTINATION: MAIN CHALLENGES

Dataset

The Bluetooth data available from the network of sensors in Brisbane is organized in tables. Each row of these tables contains an identification number of the Bluetooth device (encrypting a single MAC address), the identification number of the scanner, the time at which the device was detected and the *duration*, that is, the time period during which the device was considered to be within the scanning area. From this data, one can try to recover the actual journey of the individual vehicles, in order to estimate the Origin-Destination matrices. The following sections aim to give an overview of the difficulties of this task, and to propose a first method to overcome some of them.

Uniqueness of MAC Address

Although MAC addresses, the electronic identifier of Bluetooth devices are expected to be unique*(22)*, it appeared from the dataset that some MAC addresses are shared among vehicles. An explanation is to attribute to the possibility to clone Bluetooth devices parameters for fleet's specific needs*(23)*. It is a simple method to standardise all the devices of a fleet of vehicles. As a matter of fact, the devices that shared their MAC were also the most frequent users of the network. This

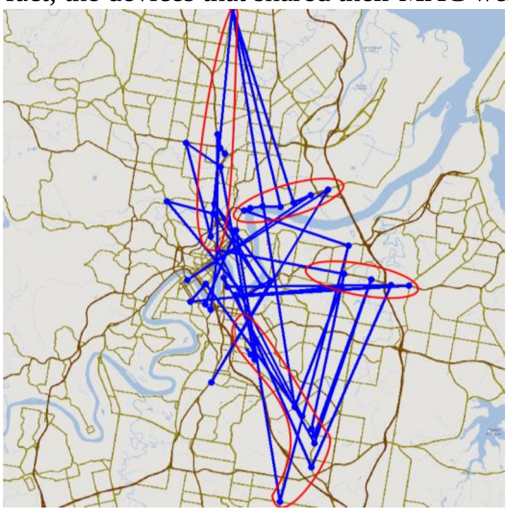


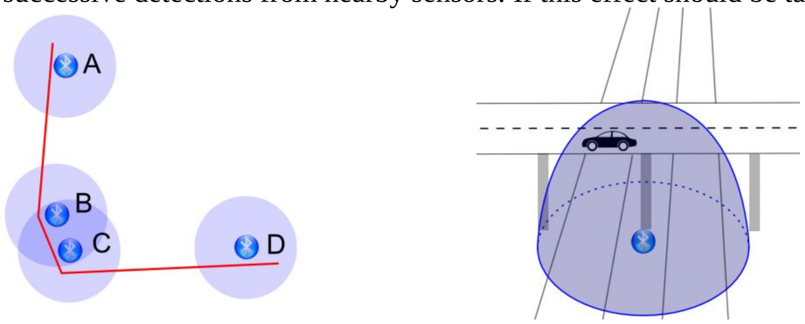
Figure 1: Real detection of a single MAC address between 6:30 and 7:00 am the 3. October 2012 (more than 50 detections scattered on this 20km x 20km area). Each link represents two successive detections. The speed computed along the links is often largely over 150 km/h. This sequence reorganised and divided by corridor shows that at least three devices are needed to obtain such sequence with reasonable speed. (red ellipses)

suggests that some MAC IDs may be shared amounts taxi drivers.

These shared MAC IDs can nevertheless be easily detected, as they will be likely to appear at two different places of the network, at very close detection times as shown on Figure 1. To this end, the average speed can be computed between the successive detections (as distance of the shortest path versus travel time). Very high speeds are indicative of 'suspicious' IDs. From the dataset, it is observed that around 30 MAC addresses were moving regularly at a speed higher than 120km/h (although the maximum speed limit on the covered network is 80km/h). As this effect concerns very few MAC addresses, they were simply removed from the dataset.

Overlapping Detections

The location of the sensor is also of great importance, insofar as the quality of the dataset collected is concerned. Firstly, sensors located in close proximity to one another can have overlapping detection zones. Accordingly, a downstream scanner might detect a device before the upstream one does, yielding erroneous patterns of travel, as shown in Figure 2 *(a)*. However, this phenomenon can be easily detected by monitoring the speed of each device along the sequence of successive detections. Anomalous speeds recorded between close-by detectors (less than 500m) are indicators of potentially overlapping scanning zones. Thus, the speed should not be taken into account, when analysing two successive detections from nearby sensors. If this effect should be taken into account



(a) *(b)*

Figure 2: (a) A car following the itinerary ABCD might be detected as ACBD. However, as AC and BD are not adjacent, an algorithm trying to recover the path of the vehicle as the one presented further in the text, will compute a path ABC,BCD with a repetition of the link BC and a very high speed on the sequence BCBC. Both criteria enable the suspicious MAC addresses to be detected easily.

(b) A Bluetooth sensor might detect vehicles travelling corridors other than the target corridor. When this happens, the detector appears wrongly as Origin or Destination for the detected device, as it will not be detected anymore in the area.

when installing the sensors, it might sometimes be justified as in our case study where the close-by detectors are covering major intersections close from each other. Thus one detector wouldn't be enough to cover these intersections and some important information would be missing.

Another issue arising from the location of the sensors is that for some of them, their detection area may span across multiple corridors. Thus, the traffic that is detected by a sensor may not necessarily belong to the target corridor.

Figure 2 *(b)* shows an example of this phenomenon. In the figure, the detected car is driving a corridor (e.g. a bridge) that is different from the target corridor (the road underneath). If this above corridor is not covered by Bluetooth sensors (as for the Pacific Motorway in Brisbane's centre), it might lead to erroneous Origin/Destination patterns. If a vehicle travelled to the city centre through a non-scanned corridor, it might never be detected before it reaches one of the scanners of the target corridor. Therefore the scanner of the target corridor that detects the vehicle will erroneously appear as the vehicle origin. Similarly, if a vehicle is leaving the city through this non-scanned corridor, the scanner will erroneously appear as its destination. Thus, this sensor will appear to be a more important origin or destination than it is actually. Such sensors should be found and corrected afterwards manually to take into account that they will be overestimated Origin or Destination. For this case study in Brisbane, however, these non-covered corridors are currently being equipped with Bluetooth sensors.

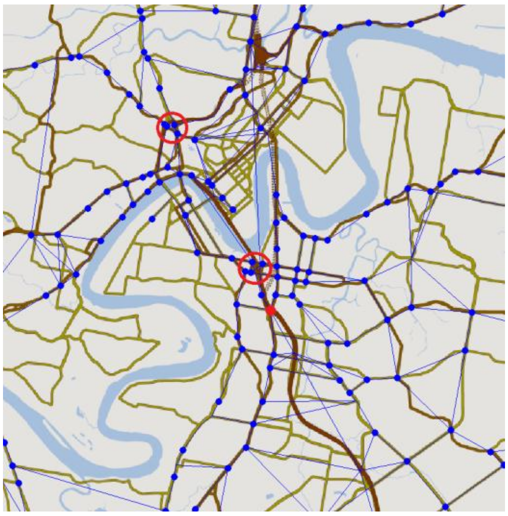
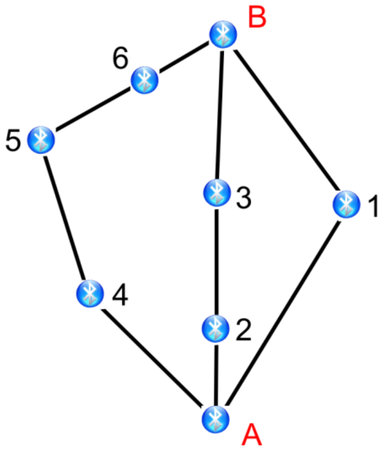


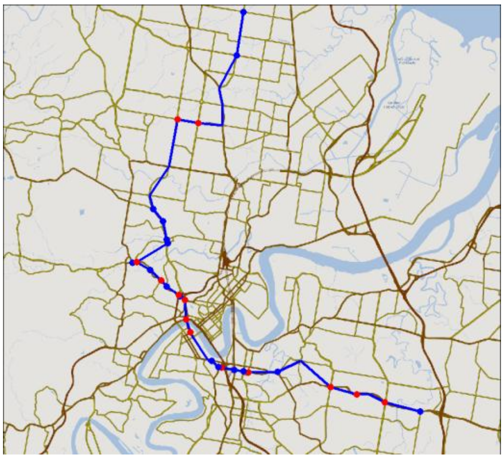
Figure 3: The red dot is a sensor located at an intersection below the Pacific Motorway but that detects also cars on it. The red circles are area where sensors overlap.

Estimation of Miss-Detections

Ideally, a Bluetooth device should be detected by every scanners of the path that is being travelled. However, the scanners might miss-detect a few vehicles. To measure the miss-detection rate, each pair of successive detections was considered. To this end, the adjacency matrix of the network (with detectors as vertices and links between the vertices when there is a direct road between the two detectors) was used as the input of the Dijkstra algorithm *(24)* to compute the shortest path between each pair of detection. Thus, the shortest path the algorithm returned was the one with the minimal number of links, that is, the minimal number of detectors, as shown on Figure 4*(a)*. The number of miss-detections was then computed as the number of vertices of the shortest path minus two (a pair of two consecutive detections). Through this method, it turned out that at least 41 percent of the detections were missing. This percentage is the lower bound as any other path, other than the shortest would have had more detectors in it.



(a)



(b)

Figure 4: *(a)* If a user was detected at sensor A and B it was detected twice whereas it should have been detected at least 3 times (in fact 3, 4 or 5 times). Therefore we know that at least one third of the detections are missing.
(b) Example of Trips with missing detections (red dots)

This result led to two major consequences: First, an algorithm recovering the missing detections had to be developed to recover the actual journeys. Secondly, it is plausible that the journeys retrieved might have wrong origin or destination, as the actual first and last detections may have been missed. This latter effect, however, will be mitigated during the process of aggregating the detectors within geographical zones suitable for Origin-Destination matrices (Statistical Local Areas).

TRIP RECOVERY

The algorithm developed to assign the sequence of detection to different journeys is based on the following assumptions.

- The distance computed between two successive detections is the length of the shortest path. This shortest path is given by the Dijkstra algorithm where the metric distance (Euclidean) is considered as the cost function (on the contrary to the above paragraph where the number of detection was the cost function). This assumption relies on the density of the network leaving very few other possibilities than the shortest path to join two detectors.
- If two successive detections are more than one hour apart, or if the average speed between them is lower than 1 km/h (provided that both detectors are further than 500m as explained above), these two detections will be assumed to belong to two separate journeys.
- If two successive detections are less than 15 minutes apart or if the average speed between them is above 20 km/h; these detections are assumed to belong to the same journey. In fact, even if a vehicle had the time to stop between two detections which are less than 15 minutes apart, such 'outlier' would not be of great importance for the purpose of the Origin-Destination retrieval exercise, as the journeys recovered will then be aggregated over a longer period of time (15, 30, 60 minutes or more) and over broader geographical zones.
- If a pair of detections satisfies the previous criterion but the detectors are not spatially adjacent, fictive detection are added, based on the shortest path (for the same reason as above).
- All sequences of detections for which every pair of successive detections satisfy these criteria belong to a first set of journeys whereas the other ones, that contain at least one pair of successive detections that does not satisfy any of these criteria belong to the second set.

RESULTS

For Brisbane's case studies, the 1.4 millions of daily detections give, after this first step, over 136 000 journeys in the first set, weighting for 55% of the detections. The other detections are shared between 30 shared MAC address, weighting for 0.2% of the detections, devices detected only once during the day, weighting for 0.9% of the detections (10% of the devices) and isolated detections, weighting for another 3.6% of the detections (the pairs composed of them and the previous detection or them and next one both satisfy the criterion of the first assumption). Finally, 40% of the detections belonged to the second set of journeys (sequences in which at least a pair didn't satisfy any of the criteria above). For many of these journeys, the first and last detections are from the same scanner or from two scanners in close proximity (less than 1 km). In that case and when only one pair of detections, from the entire sequence, does not satisfy the criteria above, it is assumed that this sequence corresponds to a short errand (a return journey). Thus it is cut in two journeys and added to the first set of journeys. At that point, the proportions respectively became 60% (detections in the first set with well-defined journeys), 0.2% (shared ID), 0.9% (devices detected once only), 4.5% (isolated detections) and 34% (detections belonging to the second set, sequences in which at least a pair didn't satisfy any of the criteria).

Two different kinds of journeys revealed

Interestingly, performing this first sequencing of the detections, gives us two set of journeys, presumably, characterizing two different kinds of behaviours. The first set (in which every successive pair of detections satisfies the first criterion) seems to be composed of journeys done mainly by commuters, as we can clearly identify the peak hours as shown on Figure 5*(a)*. In addition, more than 80% of these journeys are shorter than 10 km. To the opposite, the second set of journeys (in which every sequence of detection has at least a pair which doesn't satisfies the criteria) is spread over daylight time (7:00 am to 5:00 pm, Figure 5*(b)*) and might be due to two kind of behaviours: the users working in their car as postmen or taxi drivers for example, as 50% of the journeys are longer than 10 km or to people doing short errands during the day as 95% of the journeys have less than 3 pair of detections which doesn't satisfy the criteria of the algorithm.

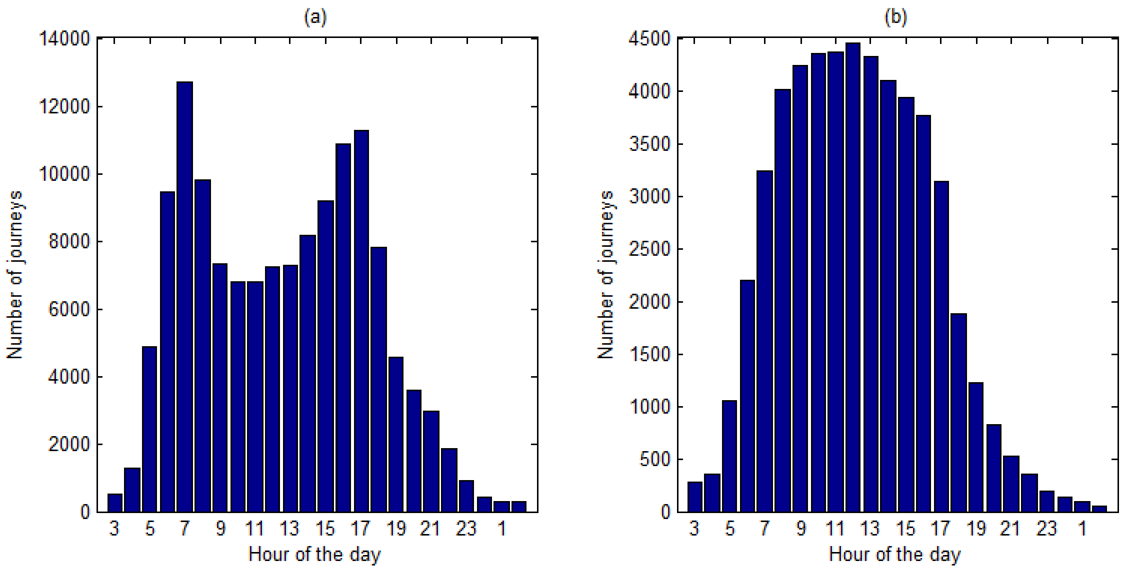
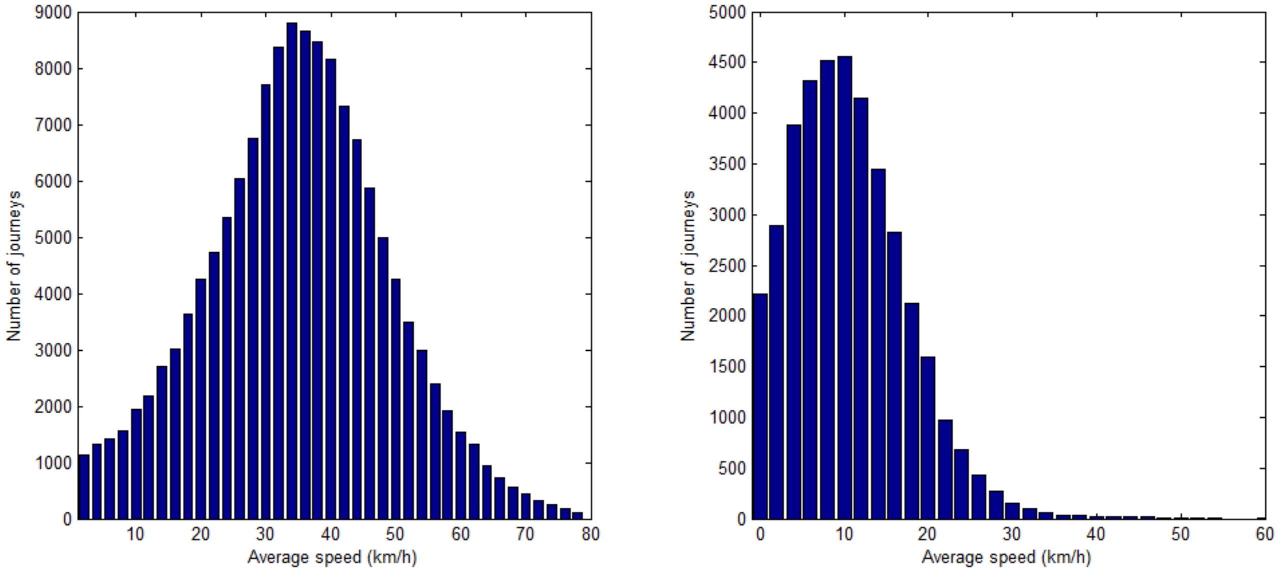


Figure 5: Reparation over the day of the journeys from both sets (set 1 on fig. (a), set 2 on fig. (b)).

Finally, the distribution of average speed for both sets, as shown on **Error! Reference source not found.**, support these assumptions as the first set (**Error! Reference source not found.***(a)*) contains journeys with higher average speed than the second ((**Error! Reference source not**



(a) (b)

Figure 6: Distribution of the average speed over the journey for both sets of detections. The first set (a) is composed of journeys with a higher average speed (mode at 35km/h) whereas the second set (b) has a mode at 10km/h.

found.*(b)*).

MISSED DETECTIONS HYPOTHESES

We suggest the following explanation to the missed detections:

- Not all scanners and devices are equally powerful, as some have stronger signals than others. From our dataset we observed that some devices were more likely to be detected, compared to others, as shown on Figure 7. This assumption is supported by the work of Porter, Kim et al.(2012) *(25)* highlighting the influence of the antenna on the signal strength and detection.
- The miss-detection rate increases, as the scanning area becomes more crowded with active Bluetooth devices. In fact, it is known that when the number of detectable devices increases,

interference may affect the effectiveness of the detection *(22, 26)*. Moreover, the maximum number of devices that can be captured is limited (3 devices per second, for the scanners located in the Brisbane area).

- The position of the detectors is of great importance, as Bluetooth signals are weakened by physical obstacle (e.g. walls and billboard). Brennan Jr, Ernst et al. *(27)* have also shown that the vertical position of the Bluetooth scanner has an influence of the effectiveness of the sensor.
- The weather as a strong influence on the signal strength.
- Not all Bluetooth devices are always in discoverable mode. (e.g. some devices may become undiscoverable after a few minutes of non-use)
- The scanners detection process can be described as an inquiry cycle during which the detector will send inquiry messages on a broad range of frequencies and waiting for devices to answer*(28)*. However, this inquiry cycle needs some time to complete. It is advised *(22, 28)* that a Bluetooth device should remain in a discoverable mode (or inquiry substate) for 10.24 seconds, within the detection zone of a scanner. Therefore, a device moving at a speed of above 72km/h have a small probability of not being detected by a scanner with a scanning radius of 100m (200m in 10 seconds). A comprehensive overview of several technical aspects on the use of Bluetooth for networks user detection is developed in *(29)*.

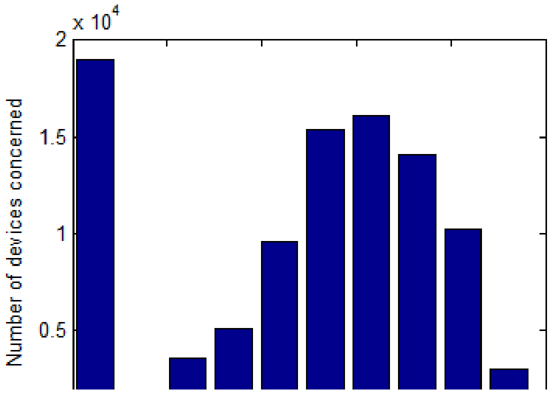


Figure 7: Two modes are observed. The first mode for a probability of being missed below 10% mainly composed of devices only detected twice by successive detectors and another at 35%.

CONCLUSION AND FUTURE WORK

This paper presented the major difficulties that are encountered when cleansing and analysing the Bluetooth data, in order to retrieve reliable OD matrices. The assigning algorithm presented in this paper is a first step toward the complete cleansing of these data. For this preliminary work, it was shown that different journeys can be distinguished through the cleansing and correction process. The density maps obtained from these recovered journeys[1] can be used to visualize the traffic conditions (e.g. saturated or under-saturated flow) of the Brisbane network. However, the extraction of other 'less obvious' patterns will need a deeper investigation.

We have argued earlier that it is not possible to directly discern the mode being used by the detected device. However, as far as the separation of the modes is concerned, Araghi, Krishnan et al. *(11)* have demonstrated that clustering methods (hierarchical, K-means and two-step) are effective to distinguish between motorized and non-motorized travel mode, in uncongested conditions. Yet, to the best of our knowledge, very little research has been conducted towards distinguishing the various travel modes, within the motorized vehicle class, by only using Bluetooth data. Par of our effort will attempt to fill this gap. Secondly, the vehicles that are equipped with discoverable Bluetooth devices represent a fraction of the entire traffic which can have particular socio-economic characteristics. This adds further uncertainty on the actual flow that is to be estimated. Our future work will also be focused on developing metrics to quantify the reliability of the estimated OD matrices. We believe that knowing the confidence of the measure is important for any decision that is to be made, upon the OD patterns that will be discovered.

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